Supplementary Online Content

eText. Segmented regression model to estimate changes in various birth-related health factors

As discussed in the text, we expected that the response to the announcement of the Universal 2-child policy would begin approximately July 1, 2016. We anticipated a phase-in period during which birth patterns began to change, followed by a plateau phase as patterns reached equilibrium. Accordingly we used segmented regression models (a.k.a interrupted time series models) reflecting a "temporary slope change leading to a level change model."[1] This approach was used to quantify changes in levels of: percent of mothers who were multiparas and that of mothers age >=35 years.

We visually inspected the monthly scatter plots for each outcome and identified the starting time point (i.e. the month when the slope began to increase) as July 2016 and the ending time point (i.e. when the slope stopped to increase) as February 2017 for the period of slope change. This generally held across the outcomes that were measured.

We developed the segmented regression models using a linear regression approach, with this specification:

$$Y_t = \beta_0 + \beta_1 \times month_t + \beta_2 \times policy_t + \beta_3 \times month\ dummy_t + e_t$$

Where Y_t is the outcome, *Month* is a continuous variable indicating time in months at time *t* from the start of the observation period (coded as 1-36, corresponding to the month from January 2015 to December 2017 for the outcomes parity and maternal age, and coded 1-24 for the outcome preterm delivery, which was added to the IDIR data series in January 2016; see text). *Policy* is a variable indicating the status of presence of the effects of the Universal 2-child policy. At the baseline period (i.e. before July 2016) *Policy* was coded as 0. After the slope stopped increasing (i.e. after February 2017) *Policy* was coded as 1. During the period of temporary slope change, *Policy* was coded as incremental values ranged between 0 and 1 with equal intervals from the starting to the ending time point, as determined by dividing 1.0 by the number of time points over the slope changing period. Specifically, *Policy* was coded as 0.125, 0.250, 0.375, 0.500, 0.625, 0.750, and 0.875 for months from July 2016 to January 2017, respectively. *Month dummy* included a set of 11 indicators, representing the 12 calendar months of a year.

Using this approach, we primarily aimed to estimate the regression coefficient of *policy* (β_2), which can be interpreted as the full change in the level of the outcome (i.e., the absolute change in the percentage points) between the baseline phase and the post-policy plateau phase.

For preterm delivery rate, we established a standard segmented regression models using a linear regression approach:

$$Y_t = \beta_0 + \beta_1 \times month_t + \beta_2 \times policy_t + \beta_3 \times month\_after\_policy_t + \beta_4 \times month\ dummy_t + e_t$$

Where Y_t is the preterm delivery rate, *Month* is a continuous variable indicating time in months at time *t* from the start of the observation period (coded as 1-24, corresponding to the month from January 2016 to December 2017 for the outcomes parity and maternal age). *Policy* is a variable indicating the status of presence of the effects of the Universal 2-child policy. At the baseline period (i.e. before July 2016) *Policy* was coded as 0 and thereafter coded as 1. *Month_after_policy* is a continuous variable, counting the number of months after the policy took effect (coded 0 before July 2016 and 1-18 for months from July 2016 to December 2017, respectively). *Month dummy* included a set of 11 indicators, representing the 12 calendar months of a year.

Using this approach, we primarily aimed to estimate the regression coefficient of *policy* (β_2) and *month_after_policy* (β_3), which can be interpreted as the change in the mean level immediately after the policy took effect and the change in the slope of the preterm delivery between the baseline and effective phase, respectively.

eTable 1. The total number of births in CMAD and total deliveries in IDIR

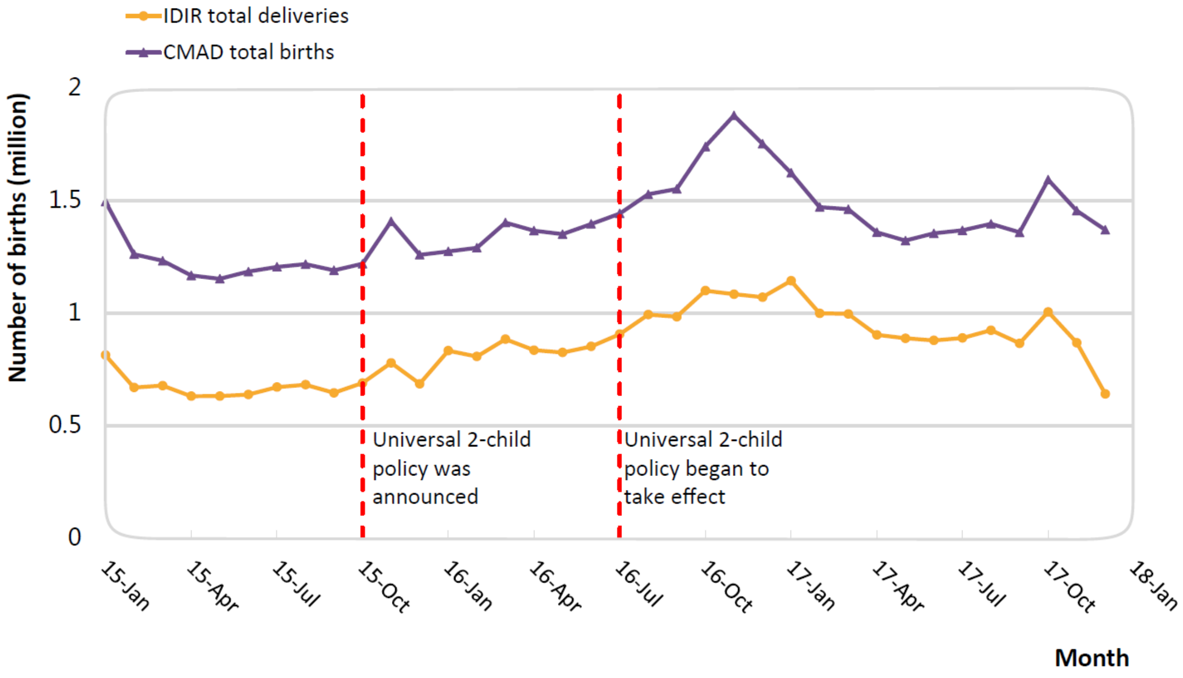
Type of restrictiveness of the 1-child policy	Number of births in CMAD	Number of deliveries in IDIR	Percentage of number of deliveries in IDIR relative to total births in CMAD (%)
Most strict	7,638,588	5,324,771	69.7
Moderately strict	39,896,810	24,271,090	60.8
Least strict	2,578,491	2,190,418	84.9

eTable 2. The modelling results of the difference-in-difference model on the number of excess births (millions)

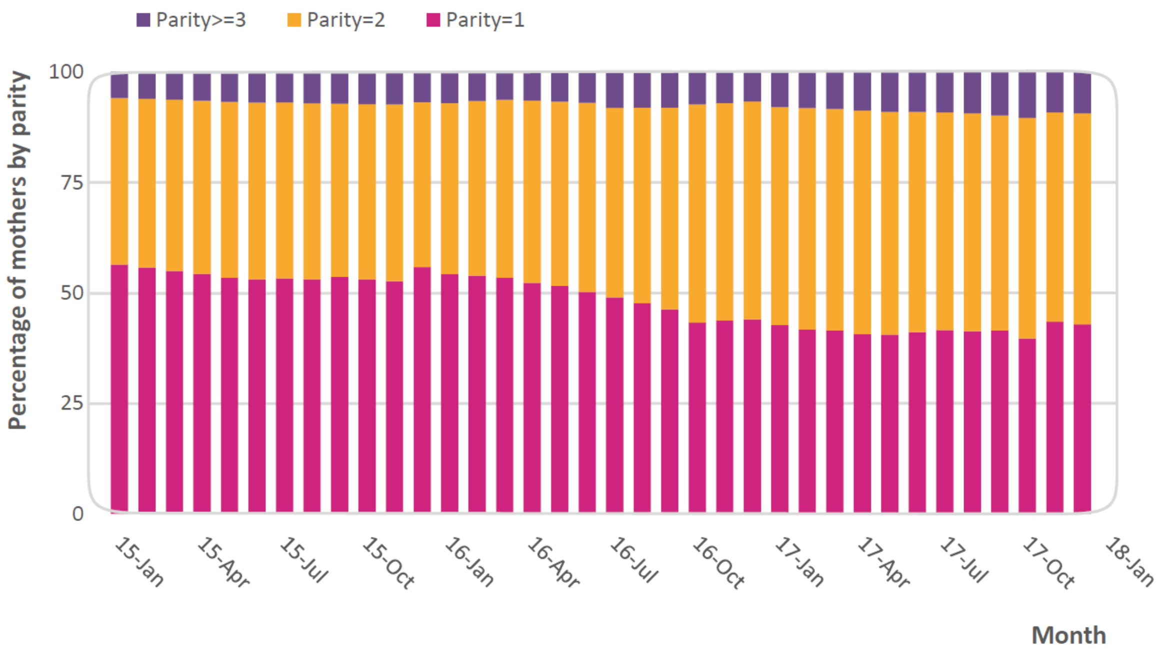
	Regression coefficient	Standard error of the regression coefficient	P value
Intercept	0.71	0.03	<0.0001
Parity	-0.09	0.02	0.0001
Policy	-0.05	0.02	0.05
Parity*Policy	0.30	0.03	<0.0001
Months			
Jan	0.04	0.04	0.35
Feb	-0.02	0.04	0.53
Mar	-0.01	0.04	0.75
Apr	-0.05	0.04	0.24
May	-0.06	0.04	0.14
Jun	-0.04	0.04	0.32
Jul	-0.06	0.04	0.12
Aug	-0.04	0.04	0.30
Sep	-0.05	0.04	0.23
Oct	0.03	0.04	0.46
Nov	0.06	0.04	0.13
Dec	0	-	-

Note: the definition and coding strategies for each variable are provided in the main text.

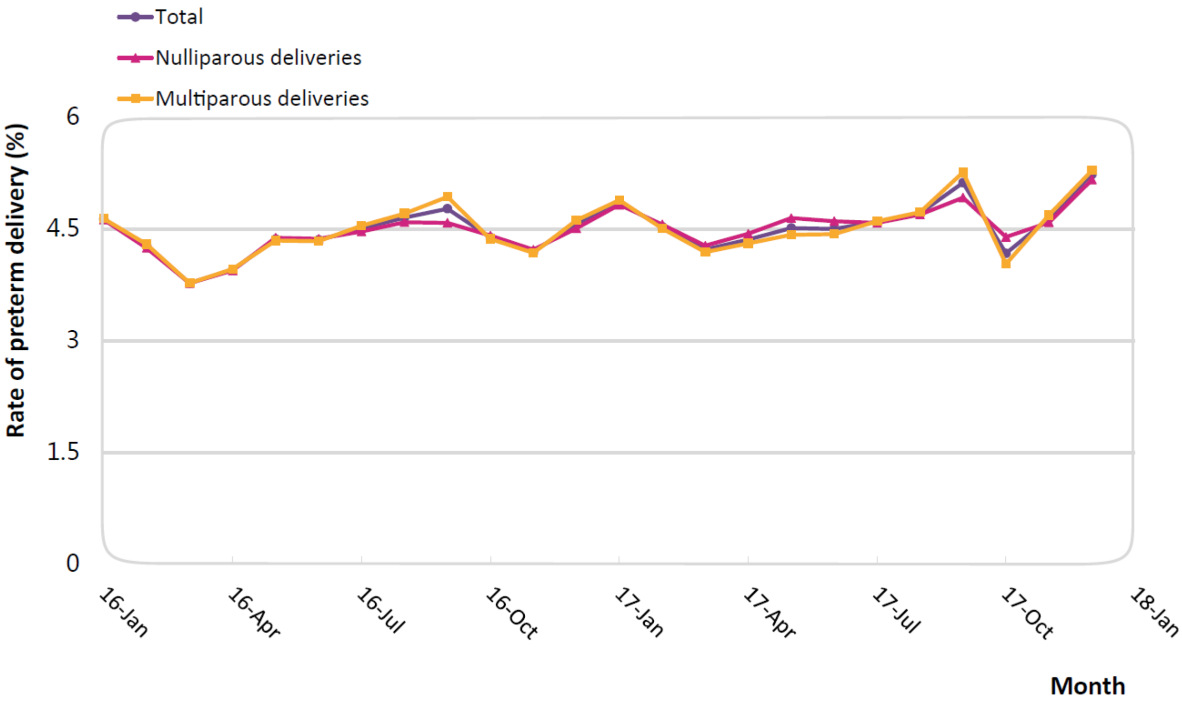
eFigure 1. Monthly number of deliveries in IDIR and monthly total births in CMAD



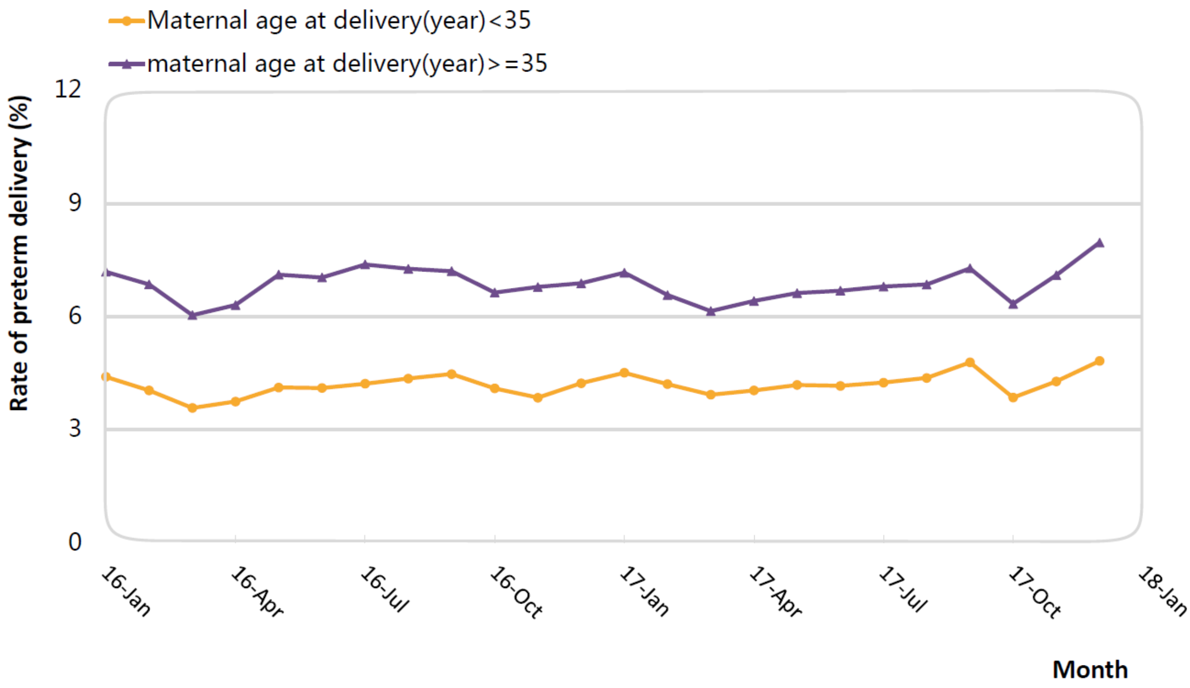
eFigure 2. Changes in the distribution of mothers by parity (%), January 2016–December 2017



eFigure 3a. Secular trends in the overall and parity-specific preterm delivery rate, January 2016–December 2017



eFigure 3b. Secular trends in the preterm delivery rate by maternal age, January 2016–December 2017



eReference

1. Bernal JL, Cummins S, Gasparrini A. Interrupted time series regression for the evaluation of public health interventions: a tutorial. Int J Epidemiol 2017;46:348-55.